Article

Modeling the Impact of Electric Vehicle Charging Infrastructure on Regional Energy Systems: Fields of Action for an Improved e-Mobility Integration

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Abstract: Since e-Mobility is on the rise worldwide, large charging infrastructure networks are required to satisfy the upcoming charging demand. Planning these networks not only involves different objectives from grid operators, drivers and Charging Station (CS) operators alike but it also underlies spatial and temporal uncertainties of the upcoming charging demand. Here, we aim at showing these uncertainties and assess different levers to enable the integration of e-Mobility. Therefore, we introduce an Agent-based model assessing regional charging demand and infrastructure networks with the interactions between charging infrastructure and electric vehicles. A global sensitivity analysis is applied to derive general guidelines for integrating e-Mobility effectively within a region by considering the grid impact, the economic viability and the Service Quality of the deployed Charging Infrastructure (SQCI). We show that an improved macro-economic framework should enable infrastructure investments across different types of locations such as public, highway and work to utilize cross-locational charging peak reduction effects. Since the height of the residential charging peak depends up to 18% on public charger availability, supporting public charging infrastructure investments especially in highly utilized power grid regions is recommended.

Keywords: charging infrastructure assessment; e-Mobility integration; Agent-based modeling; levers; global sensitivity analysis; service quality

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1. Introduction

As more and more policy targets worldwide focus on Battery Electric Vehicles (BEVs), their share will increase significantly within the next years. While the German government announced to reach 7–10 million BEVs until 2030 [1], other European countries have similar ambitions. The increase in Spain, for instance, aims at 5 million BEVs in 2030 and the United Kingdom targets a share of 50–70% of BEVs by 2030 [1].

As estimated in the Alternative Fuels Infrastructure Directive of the European Union, 0.1 public charging points per BEV are required [2]. With about 33,000 charging points in Germany in December 2020 [3], there are almost one million additional charging points to be installed within the upcoming decade.

To ensure an efficient charging infrastructure network in the long term, pathways considering economic viability, the integration into energy systems and the Service Quality of deployed Charging Infrastructure (SQCI) are necessary already today [4]. Within this context, grid operators focus on mitigating the grid impact, Charging Station (CS) operators need viable business models to develop and maintain further investments and BEV drivers need to rely on a sufficient CS network for a fair price. Since these objectives all depend on the interaction of a variety of different projected factors such as the future BEV fleet,

the CS network and the assumed charging behavior, the planning uncertainty increases. Especially, the integration of electric vehicles alongside electric heat pumps and renewable energies into the electrical grid comes with new challenges [5]. However, simultaneously, the flexibility potential of charging processes can help to integrate intermittent renewable energy sources and contribute, for instance, to the power stability in the energy system [6,7].

To cope with these challenges efficiently, we contribute by quantifying the impact of different technical levers, such as the CS availabilities and charging power, on different important measures for the e-Mobility integration into rural and urban energy systems. This is specified at the end of Section 2. Therefore, we developed a comprehensive “Agent-based e-Mobility Model” for regional charging systems representing the interaction of heterogeneously behaving BEVs and CSs at different locations (cf. Section 3). A global sensitivity analysis is applied to assess the impact of vehicle types and CS parameters on the charging demand, simultaneity factors, charging flexibility, CS utilization and SQCI (cf. Section 3). The results and discussion of the global sensitivity analysis in Section 4 helps to improve the quality of future charging infrastructure planning and e-Mobility integration processes. Finally, a conclusion and general guidelines for future CS rollouts are derived in Section 5.

2. Literature Review

In the e-Mobility literature, the uncertainty of the simultaneity of charging processes as well as the electric demand and its flexibility are mostly assessed based on a few scenario variations. Authors focus on input parameters such as regionally differentiated travel statistics, CS types, locations and availabilities as well as, e.g., BEV penetration [8–11]. Uimonen and Lehtonen [12] focus on charging demand in office buildings, Brady and O’Mahony [13] stochastic simulation including GPS data and charging behavior. Harbrecht et al. [14] and Ul-Haq et al. [15] also apply a stochastic model to investigate electric vehicle charging demand in residential areas. Further, Harbrecht et al. [14] assess factors, that impact the charging behavior.

A meta study of VDE I FNN and BDEW [16], comprising 157 scenarios, states that the simultaneity of charging processes is a key element for assessing the grid impact. Therefore, deriving consistent simultaneity factors is important and needs to be assessed fundamentally. Moreover, they conclude that the impact of charging power on the simultaneity as well as the interaction between different types of CSs at different locations is so far not adequately addressed in literature.

Furthermore, there is a variety of studies focusing on CSs from different perspectives. While Sheppard et al. [17] assess different vehicle types and driver behavior on the requirements of a CS network in Delhi, the scope of a study by Liu [18] considers only the interaction between different types of CSs. Soylu et al. [19] aim at developing a demand-oriented approach to assess the required CSs in Germany based on 6 scenarios. Moreover, while Das et al. [20], inter alia, qualitatively review potential positive and negative impacts of BEV energy system integration, Deb et al. [5] review that there are a few studies combining multi-objectives such as CS cost, grid constraints or distance between CSs. Two multi-objective charging station allocation articles are from Han et al. [21], who apply an agent-based multi-objective optimization to allocate CS within a city based on the CS availability and profitability, and from Kong et al. [22], who optimize locations for fast charging CS based on similar criteria but they include power grid restrictions.

The studies from Gnann et al., Jochem et al., Funke et al. Grube et al., Nicholas and Wappelhorst and Brost et al. [23–28] focus on identifying the demand of fast charging infrastructure or on a regional charging infrastructure allocation. However, these studies do not assess interactions between different types of charging infrastructure and the impact of different charging infrastructure network designs on, for instance, charging power and flexibility. Further studies such as from Seddig et al. and Hussain et al. exist focusing on uncertainties at parking sites. Seddig et al. use a Monte-carlo simulation to assess the integration potential of renewables energies and electric vehicles, and Hussain et al.

optimize charging activities under consideration of different criteria using a fuzzy-logic approach to deal with uncertainties [29–31].

As the diversity of publications and methods used in e-Mobility reveals [5,32,33], this complex field is highly relevant and it needs to be assessed comprehensively incorporating different views.

To the best knowledge of the authors, there is no published study in the field of e-Mobility integration into regional energy systems aiming at finding the most important technical levers to consider, while at the same time assessing charging demand, economic viability of CS and the SQCI. As a global sensitivity analysis is a well-proven methodology to quantify the impact of model inputs on model outputs [34–36], this is found to be an appropriate approach for impact evaluation of certain technical levers. The only global sensitivity analysis conducted in the field of e-Mobility assessed impact factors on the vehicles' energy consumption [37] and the life cycle analysis of BEVs [38].

While the derived factors such as the charging demand and its flexibility are only a means to an end in most studies, we aim at improving the impact assessment of these relevant factors and thereby contribute to enhancing the quality of future planning and policy guidelines.

Additionally, we contribute to the research by developing an Agent-based model being capable to assess the interaction between BEVs and CS consistently over time and space while being parametrized to represent real world regions. It allows for considering the required output to assess different views of stakeholders and comprehensively analyze their sensitivity to CSs, vehicle type and behavioral parameters such as range anxiety. Moreover, for the first time in literature, general guidelines for integrating e-Mobility with a focus on regional charging infrastructure are derived fundamentally based on a sensitivity analysis.

3. Materials and Methods

3.1. Agent-Based e-Mobility Model

The objective of the model described in this Section is to analyze the upcoming e-Mobility charging demand and the required charging infrastructure deployment within a region. For this, the driving and charging behavior of BEVs are modeled while considering CS availabilities within a spatially resolved system. An Agent-based model is applied since this model class is capable to represent spatial resolution as well as heterogeneous individuals and technologies such as BEVs and CSs as objects, so-called agents. Thereby, each agent can be parametrized, for instance, by a specific driving behavior and each CS can be placed along BEV agents' routes. While BEV agents interact with each other by occupying CSs, different CSs interact directly with BEVs by serving energy to BEVs and thus competing with other CSs in the modeled region. Therefore, this approach allows for modeling a region and to include interaction effects between different types of CSs at different locations. Additionally, consistent driving schedules of BEVs are modeled to link the temporal and spatial dimensions properly. This includes, for instance, consistent SOC over the entire simulation period and realistic simultaneity factors at each modeled location.

The basic principle of demand modeling at different locations, applied here, was published by Husarek et al. [39] in 2019. Its further development to cope with the requirement of analyzing charging infrastructure within a region is described within this Section in detail. Thereby, the following main requirements are imposed on the model development:

- Modeling spatially resolved CS availability;
- Regional parametrization and easy adoption to various regions.

To validate the model, we compared the occurring charging events of public and work chargers with measured data from 26,951 German charging stations published in Hecht et al., 2020 (cf. Appendix E) [40].

3.1.1. Model Framework

The Agent-based e-Mobility Model framework can be described by the input and output parameters of the model as well as the regional simulation setup as shown in Figure 1. The model setup allows for each agent to report every variable at any time step. To reduce the complexity of the output, the agents' output can be condensed by grouping agents and evaluating aggregated parameters. Therefore, within this study, all duplicated locations are aggregated by type and thereafter, the demand is assessed on this aggregated level. In addition, CS utilization rates are averaged over all CSs at the same type of location. The input parameters are subdivided into the four categories of general simulation parameters, regional parameters, technical parameters and behavioral parameters. Following, some input parameters are discussed and subsequently, the model setup is described.

Figure 1. Model framework of Agent-based e-Mobility Model.

Input Parameters

The BEV density depicts the ratio between the two input parameters 'number of BEV', referring to the modeled number of BEV within one simulation, and the 'number of location duplicates' indicating the modeled number of locations of the same type. We assume BEV density per location to be one important factor to define different regions within the model and therefore, we include it in the modeling process. While the standard approach in literature is to model only one location per type, this new implementation allows to consider the spatial distribution of a region.

One common challenge in modeling BEVs and their regional charging infrastructure is to consider inter-regional trips of BEVs traveling into or out of the investigated region. The number of BEVs within the modeled region depends on these inter-regional travel patterns and influences the demand as well as the required infrastructure in the region. Even though this parameter is not assessed in most charging infrastructure studies, it is considered within this paper to further define the characteristics of a region. Consequentially, three assumptions are made, which are, for convenience, described in the following for BEVs leaving the region only. The case of BEVs entering the region can be derived by inverting those rules. Firstly, inter-regional commuters leave the region during the day. Secondly, they charge outside of the region assuming a similar CS availability in adjacent regions. Thirdly, the only charging activity, which is considered for the demand within the assessed region, takes place at home. All other charging activities within surrounding regions only affect the SOC of the BEV's battery.

Conversely, the obvious parameters describing the CS supply ‘number, type and location of CSs’ are crucial for the load allocation but neglected in many studies. Additionally, some studies consider the CS supply by modeling the availability but, as stated by the Metastudy of VDE | FNN and BDEW [16], no interdependent effects of different charging solutions are assessed. Consequently, this impact is included in our analysis as described in the Model Setup and Simulation paragraph.

As highway charging is considered to be a crucial element for long-distance traveling [24], its impact on regional charging demand and infrastructure is barely analyzed in literature as stated in the meta study of VDE | FNN and BDEW [16]. Thus, the effect of different Direct Current Fast Charging station (DCFC) coverages (DCFC coverage, cf. Figure 1), in terms of distance between two CSs along highways is included in our study and described in the Model Setup and Simulation paragraph.

Although home charging is the preferred way to charge as described by Frenzel et al., 2015 and Hardman et al., 2018 [41,42], it can be restricted due to several reasons such as private parking availability or economic reasons of BEV owners. Within this model, the share of BEVs which can charge at home is defined as home charger access. It is assumed each home charger is only used by a single BEV over the entire simulation.

Model Setup and Simulation

The model is implemented in the NetLogo environment, which is a multi-agent programming language with integrated modeling environment for Agent-based models [43]. Within each simulated time step, agents move and interact with their environment and with other agents based on their predefined rules and attributes, thus causing a system behavior to emerge.

Three different types of agents are introduced in the model. Firstly, an agent type referred to as “location” is used to model a spatial resolution within the system. Each location is of a certain type, such as e.g., supermarket, leisure, work or home. These types are only restricted by the granularity of input data of the driving profiles of BEVs. To model different BEV densities, the number of location duplicates is modified. Thus, considering a constant number of BEVs, the more duplicates used, the lower the modeled BEV density is. This approach allows the model to be adjusted to different penetration levels as well as various regions with different vehicle densities.

Secondly, the CS agent is introduced. Each CS is assigned to a location whereby several CSs can be placed at the same location. The charging power attribute of a CS defines the maximum available power for charging a connected BEV. Moreover, each CS can only serve a defined number of BEVs at a time, which is defined by the initial availability. An availability of zero thereby indicates no available plugs and an availability of two is signaling that two additional BEVs can connect to the CS in this time step. Here, payment system restrictions are neglected. Contrary, if a BEV has access to a private CS at home, it is available to the BEV anytime when the BEV is at home. This assumption can be interpreted such that, at most, one BEV per residential CS is supposed.

While this concept is limited to represent CSs at modeled locations and therefore it is limited to destinations where vehicles park during the day, fast charging is not covered by this approach. This is due to the lack of fast charging activities within the daily activity schedules, which are mainly based on internal combustion cars. This approach is applied since the refueling behavior of BEVs differs fundamentally from internal combustion vehicle refueling behavior today, with BEVs predominantly charging at locations, where they park and thus, trying to avoid additional stops [41]. To cope with additionally required charging stops, a statistical representation of highway DCFC is modeled. Therefore, the probability of a DCFC station located along a trip of a BEV is regarded if the trip is longer than 30 min and the average speed for the entire trip is more than 50 km/h. Furthermore, assuming that BEVs only charge at highway DCFC stations to avoid running out of energy,

a BEV checks for a highway DCFC station along its current way only if the SOC is below 30%. The probability $P_i(t)$ with

$$P_i(t) = \frac{d_i(t)}{DCFC \text{ coverage}} \quad (1)$$

where $d_i(t)$ is the distance to be driven within this time step t describes if a DCFC station is located along the way of a BEV i . When charging, the driving schedule is assumed not to deviate and no further availability constraints on DCFC charging are imposed.

Thirdly, BEV agents represent the vehicle itself and the driver's behavior. It is characterized by the consumption, the battery technology and the on-board charging capacity. As described above, each BEV is assigned to its own home location. BEVs are the only moving agents within the simulation traveling from location to location based on their exogenously defined driving profiles [39]. The main underlying assumption of the agent's driving behavior is that the vehicles do not deviate from their predefined movement pattern, which means that the driving profiles of all BEVs are fixed as exogenous input for the simulation. Furthermore, the charging behavior of a BEV determines the rules for deciding when and where to charge. Since this analysis only covers the strategy "charge at arrival", as this is common practice in charging demand modeling literature, no other strategy is covered in this paper. Thereby, it is assumed that a BEV charges at every location where it parks—in case a CS is available at the location at this time—as soon as it arrives until the battery's SOC reaches 100% or the BEV departs (cf. Husarek et al., 2019 and Figure 2) [39].

Figure 2. Flow chart of Agent-based e-Mobility Model focusing on the BEV actions and the interactions between agents.

The simulation procedure is based on discrete time steps, whereby in each time step, several decisions, actions and interactions are simulated. BEVs are processed consecutively within a random order. This order changes within each time step to ensure that the chance

to connect to a CS before other BEVs occupy it is balanced for all BEVs over the entire simulation period (cf. Figure 2).

Each BEV executes actions based on its state—driving, parking, charging—within the time step. The basic principle of that is described in Husarek et al., 2019 [39].

It should be emphasized that vehicles continue driving even if the value of their SOC would turn negative. In this case, the SOC is fixed at zero, according to Figure 2. Although this assumption does not hold true for full battery electric vehicles in reality, we measure these ‘empty battery kilometers’ and use this as an indicator for the SQCI within a region. While we base this measure on the fact that most drivers prefer charging at their parking destination to avoid delaying trips [41], a similar indicator is used, e.g., in Nicholas et al., 2019 [44]; van der Kam et al., 2019 [45]. The lower the share of electrically driven kilometers compared to the total driven kilometers within the simulation period, the lower the SQCI. More far-reaching, McCollum et al. [46] argue and Hardman et al. [42] review in their meta studies that this indicator is additionally reasonable since a certain charging infrastructure satisfaction rate is required to incentivize the decisions to invest into a BEV [42,46]. Other authors use, e.g., the indicator of queuing time at CS or detour kilometers to reach the next CS [33].

In addition, the interaction between BEVs and CSs can be described as follows (cf. Figure 2). If a BEV parks within the current time step and if it wants to start charging according to its charging strategy, the BEV checks the CS availability at its current location. Since all CS report their changes in the availability to the location, BEVs do not need to interact with each single CS at the current location but only with the location they are parked at. Furthermore, it is to be mentioned, that if a BEV disconnects from a CS, the CS reports that it is available not directly, but at the end of the time step. This ensures that when processing the next BEV, the CS is not available within the same time step again. If there is an available CS, the BEV connects randomly to one of the available CSs at the location and starts charging, which increases its SOC according to the maximum available charging power. If the SOC would reach 100% before the time step is over, the charging power is reduced so that the SOC reaches exactly 100% at the end of the time step. This represents a simplified modeling of a charging power reduction by a battery management system, which usually is applied to increase the battery lifetime.

3.2. Procedure and Experimental Data

As summarized in Figure 3, the above introduced Agent-based e-Mobility Model is applied to two different regions and its sensitivity to BEV and CS parameters is quantified applying a Sobol sensitivity analysis accompanied with a correlation analysis. To comprehensively assess the impact of e-Mobility integration in both regions, three stakeholder perspectives are investigated by means of 17 output parameters. For this multi-output approach, the Sobol indices must be calculated for each output parameter and each modeled area individually.

Figure 3. Impact assessment procedure.

Following, the procedure of the sensitivity analysis in combination with the correlation analysis is described in Section 3.2.1. Subsequently, the experimental data for the two considered regions and 11 input parameters including their intended range for the sensitivity analysis are explained in Sections 3.2.2 and 3.2.3, respectively. Finally, Section 3.2.4 introduces the 17 key model output parameters, which are used to quantify the impact of e-Mobility from different perspectives.

3.2.1. Multi-Output Sobol Sensitivity and Correlation Analysis

The entire Sobol sensitivity analysis is applied using the SALib Python package [47]. The Sobol method was chosen since this is a proven and efficient global sensitivity analysis approach in literature [34–36,48]. Additionally, this approach is based on variance decomposition being able to handle the non-linear and non-monotonic behavior, which is inherent in agent-based modeling [35,48]. Therefore, the total variance V_T of the investigated output parameter over all simulations is decomposed into the partial variances V_i that are caused by only varying one parameter i while not changing other parameters and the higher order partial variances that are computed by varying two or more parameters $i, j, \dots m$ as indicated in Equation (2) [49].

$$V_T = \sum_{i \in I} V_i + \sum_i \sum_{j > i} V_{i,j} + \dots V_{i,j,\dots,m} \quad (2)$$

The first order sensitivity measure of a model output to an input parameter, the so called first order Sobol index S_i , measures the contribution of that single input parameter on the output variance. It can be written as

$$S_i = \frac{V_i}{V_T}, \quad (3)$$

with $0 \leq S_i \leq 1$ while the total order Sobol index $S_T > 0$ is calculated by

$$S_T = 1 - \frac{V_i}{V_T}. \quad (4)$$

Since the Sobol total order index includes first order and higher order effects, it measures the total impact of a variable on the output variance including all interaction effects with other parameter variations. This is why we focus only on the total order index.

As the computational effort is important when applying a global sensitivity analysis due to the high number of required simulations, an efficient experimental design needs to be achieved. For that, the Saltelli sampling method is applied, which is commonly used in combination with the Sobol analysis. This method results in $N \cdot (2m + 2)$ simulations with N referring to the sample size and m denoting the number of input parameters. For each parameter, $N \cdot 2$ values are drawn from a uniform distribution within the parameter range.

To obtain the accuracy of the Sobol indices, a bootstrap method [50] is used to create confidence intervals based on 100 resamples.

In addition to the Sobol total order indices, the Pearson Correlation Coefficient is calculated. Thereby, only the sign of the coefficient is interpreted and combined with the Sobol total order index, which has always a positive sign. By this, the total interpreted indices can become negative. This combined approach allows not only to quantify the share of explained output variance, it also indicates the direction of the correlation. Hence, statements regarding whether an increase or decrease of the parameter is desired can be derived.

3.2.2. Regional Parametrization and Reference Scenario

The model is applied to two different regions in Schleswig Holstein, a federal state of Germany. Among them, one rural region and one urban region depicting the municipality of Steinburg and the state's capital of Kiel, respectively. All regionally differentiated travel statistics and driving profiles used are from MiD, 2017 [51] and based on the "Regional Statistical Spatial Typology for Mobility and Transport Research" (RegioStaR) of the Germany Federal Ministry of Transport and Digital Infrastructure and the German Federal Ministry for Building Transport and Urban Development. Within this typology of municipalities, Steinburg is classified as a small-town area and village area and Kiel is classified as regiopolis. These regions reveal fundamental structural differences for the e-Mobility integration including the population density with Steinburg counting 124 citizens per km² and in Kiel, 2080 citizens per km² as well as differences in travel statistics, for instance, the average traveled distance to work being 2.4 times larger in Steinburg compared to Kiel (MiD, 2017) [51]. Additionally, 23% of commuters are leaving the municipality of Steinburg during the day whereas 36% of commuters from surrounding municipalities enter Kiel during the day. Those are referred to as inter-regional commuters in the model (cf. Figure 1) and in Table 1. To compare the results in both regions, the BEV penetration rate is assumed to be 10% in both regions, which results in 8400 BEVs in Steinburg and 11,000 BEVs in Kiel. Table 1 shows the regional input parameters used for setting up both regional models.

Table 1. Rural and urban regional parameter set considering 10% BEV penetration.

Regional Parameter	Rural	Urban
Driving profiles (MiD, 2017) [51] filtered by municipality type	Small-town area, village area	Regiopolis
Home charger access	84%	60%
Share of commuters	49%	46%
Inter-regional commuters	−23%	36%
BEVs in region	8400	11,000
BEVs per public location	24	15
BEVs per work location	37	67
BEV penetration	10%	10%

To get the number of vehicles per location, it is required to count the potential public and work charging locations and relate them to the number of BEVs in the region given the projected penetration of 10%. For work locations, it is assumed that coherent areas of type industrial, commercial and retail offer joint BEV parking hubs to increase investment efficiency and thus only the number of areas is counted. Public charging, in contrast, is assumed to occur mainly at points of interest such as public parking, supermarkets, restaurants, refueling stations, etc. To avoid overestimating the number of potential charging locations within a region, all locations being in walking distance to each other, based on an overlaying 150×150 m raster, are counted as a single potential charging location (cf. Appendix D).

Finally, rural and urban areas differ in the potential access to private chargers at home. To account for this effect, the potential home charger access is determined based on the share of vehicles having access to private parking at home, e.g., a garage. These data are available in MiD, 2017 [51], for the level of RegioStaR typology of municipalities for Germany. Bearing in mind that not every private parking space is eligible for a private CS and not every BEV owner installs one, the possibility of on-street charging in residential areas is assumed to counterweight this. Finally, the driving profiles are obtained from MiD, 2017 [51], which provides daily activity schedules based on interviewing 316,000 people. Within this study, the original trip data are used, consisting of consecutive trips of drivers over the course of one day. These data include start and end time of each trip, distance travelled, speed and purpose of the trip. Hence, realistic daily schedules are obtained and subsequently classified in commuter and non-commuter profiles and separated by region as indicated in Table 1.

For both regions, the impact of technical input parameters on the model output is assessed by means of a global sensitivity analysis (cf. Section 3.2.1). To classify the varying model output in order of magnitude for both regions, a reference scenario is simulated using a default set of vehicle and CS parameters (cf. Table 2). This reference scenario is constructed based on an e-Mobility distribution grid impact study published by the German think tank Agora Verkehrswende [52]. Vehicle type parameters are clustered into small, medium and large vehicles, which are assumed to have 40%, 40% and 20% market share, respectively.

Table 2. Reference case parametrization.

Regional Parameter	Rural and Urban Value
Number of work chargers	80 (40 stations)
Number of public chargers	80 (40 stations)
DCFC coverage	50 km
Charge power home	11 kW
Charge power work	11 kW
Charge power public	11 kW
Charge power highway	350 kW
Vehicle consumption	small: 16 kWh/100 km medium: 20 kWh/100 km large: 24 kWh/100 km
Battery size	small: 40 kWh medium: 60 kWh large: 80 kWh

3.2.3. Sensitivity Input Parameters

The model input parameters to be investigated in this study cover vehicle type parameters, CS parameters as well as regional parameters. In the process of identifying the range for each parameter variation, upper and lower bounds used in literature served as orientation. Table 3 summarizes all identified parameter ranges. The upper limit for the battery size of 100 kWh is based on Robinus et al., 2018 [53]; VDE | FNN and BDEW, 2018 [16], and exceeds the projection of 80 kWh for 2030 from the IEA slightly [1]. To avoid varying parameters, which only influence the energy consumption such as the ambient temperature, these factors are included in the energy consumption for this sensitivity. In accordance with that, the lower bound refers to the lower value of 12 kWh per 100 km found in literature without factoring in temperature effects, and the upper value of 40 kWh is based on the upper value of 26 kWh per 100 km multiplied by a temperature factor of 1.54, which is derived from Schmidt, 2016 [54], for -5°C at an average speed of 50 km/h. For the range of charging power, standard values are chosen. For the assumed distance between highway chargers, referred to as DCFC coverage, 0.1 km increases the probability of a CS along a BEV's route to almost 100% whereas 200 km distance means that a BEV, which drives 13 km (the average traveled distance in rural areas to work is approximately 13 km according to MiD, 2017 [51]) has, with a probability of 6.5%, a charging opportunity on its way (cf. Equation (1)). The number of work and public chargers is set to reach approximately the same BEV per CS ratio for work and public chargers. Since only 49% and 46% of BEVs are considered to be commuters, the number of work CSs is half the number of public CSs. Additionally, CSs are modeled to have 2 charging plugs per station. This number is not altered and hence increasing the number of CSs by one increases the number of charging plugs in the model by two.

Table 3. Parameter variations used for the global sensitivity analysis.

Input Parameter	Minimum	Maximum
Battery size	25 kWh	100 kWh
Energy consumption	12 kWh	40 kWh
Charge power home	3.7 kW	22 kW
Charge power work	3.7 kW	22 kW
Charge power public	11 kW	50 kW
Charge power highway	50 kW	350 kW
Home charger access	30%	100%
Number of work chargers	0	250
Number of public chargers	0	500
DCFC-coverage: Distance between highway chargers	0.1 km	200 km

3.2.4. Key Model Output Parameters

For e-Mobility integration, diverse output parameters are of interest depending on the perspective. This paper aims at assessing the impact of 11 input parameters on the energy system integration of e-Mobility, economic viability of CSs and the SQCI for the BEV driver based on the following 17 output parameters as listed in Table 4.

Table 4. Key measures to assess the impact of e-Mobility. ESI—Energy System Integration, ECV—Economic Viability of CS, SQCI—Service Quality of deployed Charging Infrastructure.

Output Parameter	Relevant Perspective	Description
Peak load system	ESI	Charging peak load based on the aggregated electricity demand of all CSs within the region.
Peak load home, work, public	ESI, ECV	Charging peak load based on the aggregated electricity demand of all CSs at location home, work or public, respectively.
Peak load highway	ESI, ECV	Charging peak load based on all charging processes at highways.
Simultaneity factor at home, work, public	ESI	Maximum occurring simultaneity of charging processes measured by dividing the occurring peak load through the maximum possible charging peak at this location.
Daily energy served at home, work, public, highway	ESI, ECV	Daily energy served within over all CSs at the specified type of location.
Daily shiftable energy	ESI, ECV	Daily shiftable energy (flexibility) measured according to Husarek et al., 2019 [39].
Average delay time	ESI, ECV	Aggregation of all possible delay time of all charging processes within each time step as in Husarek et al., 2019 [39], and averaging over the course of the week.
Average CS utilization rate at work, public	ECV	Averaged utilization of CSs measured by the total energy served over one week divided by the maximum potential energy that could have been served.
Service quality of charging infrastructure (SQCI)	SQCI, ECV	Share of electrically driven kilometers within the simulation period (cf. Section 3.1.1).

4. Results and Discussion

In this Section, the uncertainty of the 17 output parameters is assessed (cf. Section 3.2.4) and technical levers are identified for the integration of e-Mobility in rural and urban areas. Consequently, general guidelines for the e-Mobility integration are derived and discussed in Section 5.

4.1. Urban and Rural Reference Scenarios

A reference scenario is parameterized according to Table 2 and applied to one rural and one urban area as described in Section 3.2.2. The core model output to derive the main measures for assessing the impact of e-Mobility is the temporally and spatially resolved charging demand, which is aggregated per location to reduce the number of output parameters and to ensure comparability with literature. Figure 4 shows the hourly resolved demand for the rural and the urban region for an exemplary weekday aggregated over the assessed locations of home, work and public for 1000 BEVs. Subsequently, this aggregation level is referred to as system level and hence, the charging peak load on system level is referred to as system charging peak. Highway charging is shown separately since it is not assumed to occur in the same region. The continuous lines show the mean charging power over 100 samples conducted for the reference scenarios, whereas the shadowed areas indicate the standard error. It reveals that the system charging peak occurs at 5 pm when BEVs start charging after returning home in the evening. While in the morning hours, the charging power normalized to 1000 BEVs is in urban and rural areas below 450 kW, the

evening peak in the rural area is 1.5 times larger compared to urban areas. This translates to an urban peak to average ratio being 33% lower compared to rural profiles, which can mainly be traced back to the higher demand when vehicles return home in rural areas due to better home charger access and longer travel distances.

Figure 4. Reference scenario Charging Demand for one exemplary weekday within a rural and an urban region. The lines show the average over all 100 simulations of the reference case and the shadowed areas show the standard deviation for each hour of the day.

4.2. Model Output Parameter Uncertainties

The Saltelli sampling method is applied to the input parameters with their corresponding range as shown in Table 3. Therefore, a sample size N of 400 is applied to reach robust Sobol indices as shown in Appendix A. With 11 input parameters, this results in 8800 simulations per region. Based on these simulations, the impact of the assessed technical levers (cf. Table 3) on the key output measures (cf. Table 4) can be quantified.

Hence, the charging peak and the integral over the temporally resolved demand, referred to as energy served in the following, remains of interest. Moreover, we assess the charging simultaneity at home, work and public, the average utilization rate of CSs at work and public as well as the SQCI (cf. Table 4).

The box plots in Figure 5 show the output variation for all investigated output parameters and for both modeled regions. In addition, the reference scenario is shown as a triangle in the same plot. Overall, a strong variation in output over all simulations is observed.

Figure 5. This plot shows the possible range of key e-Mobility output parameters resulting from 8800 simulations in the course of the global sensitivity analysis as well as the comparison of the potential output variations to the parametrized rural and urban reference case. The subfigures show (a) the charging peak 1000 BEVs, (b) the daily served energy, (c) the simultaneity factor, (d) the average utilization of work and public CS, (e) the daily shiftable energy within the region, (f) the average delay time of shiftable energy and (g) the SQCI. The values in (a,b,e) are normed to 1000 BEVs. All subfigures show box plots with whiskers; outliers are defined by factor 1.5 times the interquartile range past the low and high quartiles.

Figure 5a shows that rural and urban charging peaks differ primarily in system peak and home peak. Additionally, highway charging is comparatively low since only 1000 BEVs from one region are assessed whereas usually, these stations would serve multiple regions. Moreover, strong variations for the peak load, e.g., on system level between 400 kW and 2300 kW per 1000 BEVs occur. The charging peak in the reference scenario ranks around or below the first quartile but for highway and home charging, it ranks around the third quartile.

There are no fundamental differences revealed for simultaneity factors in rural and urban areas but while at home, the simultaneity varies between 2% and 31%; for work and public, the full range between 0% and 100% is observed (cf. Figure 5c). This difference occurs primarily due to the fact that home chargers are not shared among BEVs but public and work chargers are. While the reference scenario for home and work charging coincides with median at around 8% and 37%, the public simultaneity of the reference scenario ranks close to the third quartile at 37%.

Figure 5b shows that, on average, home and public locations serve more energy in rural regions, but work locations serve more in urban areas. This can be explained by the additional commuters traveling to work from rural to urban areas. Further, highway charging seems more important in urban areas with 1.9 times the energy served, on average, compared to the rural area.

Figure 4e reveals that the amount of shiftable energy in rural regions varies between 3000 and 13,000 kWh per day. The mean observed urban flexibility, in contrast, is lower by 1000 kWh per day. Moreover, without revealing regional differences, this daily shiftable energy shows an average delay time between 5.5 h and almost 8 h (cf. Figure 5f).

The median of the average utilization for work in rural areas is at about 7%, being slightly larger in urban areas and in public at 3% (cf. Figure 5d). As the outliers reveal, the utilization at work can go up to 60% in work areas and up to 37% at public locations. The reference scenario ranks around the median for the work location and close to the third quartile for public locations.

Finally, as shown in Figure 5g, the SQCI varies between 75% and 100% with the reference scenario being at about 99.5% at the third quartile. For the entire parameter range, a slightly lower service quality in urban areas occurs. Thereby, it is to mention that 99% is assumed to be a very good quality, since this means that 99% of all kilometers can be driven electrically without deviating from the BEV's driving schedule.

4.3. Impact Quantification

Following, the impact assessment of different levers based on the Sobol indices with the direction of correlation are assessed.

Figure 6 shows the total order Sobol indices for all investigated input-output combinations multiplied with the corresponding sign of the correlation revealed from the Pearson Correlation Coefficient (Appendix B), (cf. Section 3.2.1). The values thus obtained can now be interpreted in two ways. Firstly, the absolute values are the Sobol indices and can be interpreted as the share of output parameter variance that can be explained by the variation of the input parameter in the corresponding row. Secondly, as indicated by color and sign, the direction of the input-output relation can be observed, allowing to derive statements whether an increase or decrease of the input parameter is beneficial. The sign itself does not indicate whether the correlation is beneficial or not, but in a subsequent interpretation step, this derivation can be made. Further, the confidence interval for all shown Sobol indices obtained from bootstrapping based on 100 resamples is shown in Appendix C.

Figure 6. Total order Sobol indices including correlation trend for (a) rural and (b) urban regions. Red color indicates a positive correlation between input and output parameter; blue color indicates a negative correlation. Units in the input and output variable names are only for better understanding of the parameters but are not directly related to the total order Sobol indices' values in this figure.

In the first two rows, a and b imply that the energy consumption is the most or second most influential input parameter of all investigated parameters for 12 out of 17 outputs with a positive correlation for all these parameters but SQCI. It shows, e.g., that an increasing consumption is likely to increase the peak load at all locations significantly, especially on system level with 85% (78% urban) explained variance in rural regions. Moreover, it

increases the demand for CSs which is reflected in the large negatively correlating impact explaining 44% (45% urban) of the SQCI variance. In contrast, a high energy consumption of vehicles can be beneficial for the available flexibility within the region. For rural areas, the explained variance by this parameter is 86% for the daily shiftable energy, at least 41% or the energy served at all locations as well as 18% and 13% for the average utilization of CSs at work and public places, respectively. The influence of vehicle's energy consumption in urban areas is observed to decrease for 12 output parameters compared with the rural area. Especially for the peak load at public places, the impact decreases from 50% to 39%. The impact of the battery size is mostly relevant for the SQCI, explaining more than 55% of its variance.

As rows 3 to 6 reveal for rural and urban areas, the charging power at a location only affects output parameters at the same location significantly. With increasing charging power, the peak load at the same location as well as on system level increases, but with a few exceptions, all other outputs decrease. In particular, the charging power at work and public CSs explain 11% each of the corresponding peak load, up to 66% of the simultaneity factor at the same location, 10% of the average delay time, and 39% explained variance at work and 22% at public locations of the utilization at the same location. When comparing the charging power impact at different locations, it shows that the impact on public locations is distinctly lower compared to work and home with, e.g., about 45% lower Sobol indices for the outputs' peak load and utilization and more than 60% lower for the simultaneity. The influence of the charging power in the urban area increases compared to the rural area for all outputs except for the delay time, e.g., due to shorter and more parking stops. In fact, the Sobol indices increase in urban areas more than 45% for home and public peak load, 25% for the simultaneity at public (no increase for other locations) and 23% increase for the utilization of public CSs. Finally, a neglectable impact on the SQCI and the energy served at all locations, but highways can be observed due to typical low recharge demand and long parking sessions.

One exception is that the delay time increases with increasing charging power at work, but it decreases for all other locations. This might be due to the fact that the increased power at, e.g., public locations increases the energy served at these locations, where usually short delay times occur. Compared to other locations, the highway charging power impact on the highway peak load is significantly higher with 50% explained variance (55% urban).

Summarizing the impact of charging power, it can be stated that except for highway charging and the utilization rate, the charging power is significantly less influential compared to vehicle parameters and the number of CSs being installed. Further, installing CSs with higher charging power increases the peak load and reduces the ECV without significantly impacting market volumes for CSs or the SQCI in the region.

Proceeding the analysis with rows 7–10, it reveals that the number of CSs impact the peak load strongly at the same location where the CSs are installed with at least 48% explained variance. Thus, it is the most influential parameter on the individual peak loads at locations. The impact of the number of CSs at non-residential charging locations on the peak load of these locations in urban areas is 7.5% at work and 23% at public, larger compared to rural areas. Furthermore, the home charger access is the main influence of all charging technology parameters for the system peak. In contrast, installing CSs at public locations shows with 7%, the least impact on the system peak compared to installations at other locations. On the contrary, in urban areas, the number of public CSs affects the system peak load variance with 19%, at least twice as strong compared to other CS parameters and three times compared to rural areas. The difference in rural and urban regions is due to the number of public locations, the number of non-residential charging processes and the BEVs from surrounding areas. Therefore, more public CSs directly result in more load being served and a higher simultaneity. Additionally, the public charging demand coincides temporally with the peak load of home charging, whereas work charging does not. Aside from that, the trend of affecting outputs at the same location continues for simultaneity factors at public and work. While the number of chargers at home (41%) and

public (59%) affect the average delay time strongly but with different directions due to the fact that increasing public charging increases the number of charging processes with short delay times, home (11%) and work (6%) are the only locations where the number of CSs affect the shiftable energy noticeably. That is since public and highway charging almost offer no flexibility as stated in Babrowski et al., 2014 [8] and Husarek et al., 2019 [39]. Further, the utilization at work is affected 7% stronger in urban areas but at public, 7% less compared to rural areas. Finally, while the SQCI is mainly impacted by the number of highway CSs (13%) in urban areas, the number of public CSs reveals the strongest impact (19%) in rural areas.

It should also be emphasized that there are cross-locational effects when installing CSs at one location. While public CSs explain a large share of variance (18%) of the home charging peak, work chargers explain 10% and 7% of home and public peaks, respectively. This effect is stronger in urban areas. Additional home chargers, in return, reduce the work (5%) and public peak (7%), and the latter impact increases in rural areas to 10%. Summarizing, cross-locational effects are the third most important parameter when assessing the peak load and energy served at home and work as well as the simultaneity at home. However, highway charging reveals no cross-locational effects.

5. Conclusions and Implications

As e-Mobility penetration rises and charging infrastructure is built up worldwide, the necessity to comprehensively understand the impact of different technical levers on the energy system integration, the economic viability of CSs and the quality of service is increased in a similar manner. Therefore, an Agent-based e-Mobility Model is introduced to model BEVs and required infrastructure consistently and comprehensively. We applied a global sensitivity analysis varying 11 input parameters and first, analyzed the uncertainty of 17 key parameters to be considered for e-Mobility integration policies and charging infrastructure planning. Secondly, we quantified the impact of these parameters and listed the main findings below.

Key outputs

- Differences in urban and rural areas exist, particularly evident in the charging peak and the charging station utilization;
- Highway charging especially in urban areas required with, on average, 1.9 times more highway charging demand;
- High charging peak uncertainty with expected aggregated regional loads between 400–2300 kW per 1000 BEV;
- High availability of daily shiftable energy with, on average, 7000 kWh in rural areas and a feasible load shift between 5 and 8 h;
- Relatively low utilization rates of public chargers expected with a mean of 7% (urban) and 3% (rural).

Impact factors on key outputs

- Energy demand and battery size of BEVs are the main driver for the required charging infrastructure.
- Charging power (except highway) explains less than 16% of the peak load variance and is therefore significantly less influential compared to BEVs' energy consumption and charger availability;
- Highway charging peak load is explained by up to 55% by highway charging power;
- Residential peak load explained by up to 51% by home charger access;
- Cross-locational effects matter: home charging peak explained up to 18% by public charger availability;
- Low effect of charging station parameters on shiftable energy, but the average delay time is explained up to 59% by charger's availability;
- Highly competitive market: number of public chargers explain up to 69% of the utilization of public chargers.

In the following, we discuss general guidelines for enhancing the quality of future pathways and policies.

1. **Energy system integration:** The higher the average consumption of the actual vehicle fleet, the more critical it is to utilize the simultaneously increasing flexibility potential of charging processes by efficient control mechanisms. Considering the significance of the BEVs' energy consumption, all grid assessment and flexibility studies need to be assessed with respect to their assumptions referring to the usable flexibility potential. In deeply decarbonized energy systems, the value of increased flexibility from charging processes for the integration of renewable energy sources could exceed the impact of the increased charging demand due to an increased temporal oversupply of renewable power. In addition, the flexibility of charging processes in rural areas tend to be greater by 16% compared to the urban areas, revealing great potential for future distributed energy systems and direct alignment with rooftop photovoltaics. Furthermore, while the number of stations at one location is the strongest lever (48–71%) for the peak load at the same location (250–2000 kW per 1000 BEVs), it also attenuates the peak load at other locations significantly with up to 18%. Therefore, we recommend to scatter investment incentives across a variety of different locations to distribute the upcoming charging demand. Holistic modeling approaches must be used to assess these locations and finally, to improve the allocation efficiency.
2. **Economic viability of charging infrastructure:** In particular, the projected energy consumption and battery sizes are strong indicators for the potential infrastructure market volume within a region as well as for the economic viability of CSs. Higher charging power can decrease the economic viability of stations since it comes with higher technology cost, higher grid fees and reduced utilization. Moreover, the average utilization of public charging points is significantly affected by their distribution at other locations especially public (up to 69% impact) and home (up to 7% impact). Hence, we recommend for further roll outs to consider that a higher charging power can impair the business case of charging operators without significant positive impacts on the quality of service. Additionally, competition between different locations must be investigated carefully before building up an extensive infrastructure to enhance the long-term investment security.
3. **Service quality of charging infrastructure (SQCI):** The SQCI is predominantly affected by the vehicle fleet within a region. That is why BEV market projections should be studied concisely when assessing the charging infrastructure needs within a region. Regions with expected higher energy consumption, e.g., due to extreme climates or long travel distances require more CSs, which increases their market volume. This study found two fundamentally different approaches for increasing the SQCI for rural and urban areas most effectively. That is, that urban areas' SQCI can be enhanced by implementing DC fast charging stations (13% impact) with high charging power while rural areas' SQCI should be tackled with more focus on public locations (19% impact). Further studies should reveal the different costs of improving SQCI by implementing those measures.

Further research in this field should aim at identifying the grid parameters' peak load and flexibility down to different grid areas. This should also include the incorporation of geographic information system data analysis to identify specific grid congestion areas within a region. Additionally, future work should derive specific charging infrastructure network requirements considering the SQCI, peak load and flexibility simultaneously for rural and urban areas. Thereby, a holistic consideration of integrated renewable energies, electric vehicle charging and other new electrical loads such as heat pumps is necessary.

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Abbreviations

BEV	Battery Electric Vehicle
CS	Charging Station
DCFC	Direct Current Fast Charging
SOC	State of Charge
SQCI	Service Quality of deployed Charging Infrastructure

Appendix A

Figure A1. Sobol total order indices in dependency of the number of simulations. The number of simulations is determined by the Saltelli sampling method with N = sample size and p = number of variables.

Appendix B

Figure A2. Pearson Correlation Coefficient Matrix for (a) rural and (b) urban.

Appendix C

Figure A3. Confidence Intervals of total order Sobol indices obtained from bootstrapping with 100 resamples (a) rural and (b) urban.

Appendix D

Figure shows potential CS locations in Kiel. Each raster segment in figure containing one or more points is considered as one potential location. While dots indicate points of interest, which are considered as relevant for CS allocation, as found in Open Street Maps, darker colored raster segments indicate more counted points within that segment. Therefore, high potential raster segments are colored with a darker red.

Figure A4. Identification of potential charging locations for the city of Kiel to be considered based on a 150 m × 150 m raster.

Appendix E

To validate the model, the simulation output is compared to collected data of charging events from 26,951 charging stations in Germany [40]. Therefore, we use the published data from Hecht et al [40], of the number of charging events starting within each 20 min period over the course of a week. The published data are averaged for each time stamp (e.g., all Monday 8 a.m. values are averaged). We use the data for chargers between $12 < P \leq 25$ kW, which consist not only of public chargers but also of industrial or work chargers, respectively. The 20 min measures were added up to compare it on an hourly basis with the Agent-based e-Mobility Model. We measure new occurring charging events in the simulation for work and public chargers, parametrizing the model to a 1% BEV penetration and using the entire pool of driving profiles for Germany from MiD, 2017 [51], without regional differentiation. Figure A5 shows the correlation of the data of Hecht et al. [40] and the Agent-based e-Mobility Model. A good overall match of the simulated charging events and the real data can be seen with a correlation coefficient of $r = 0.959$.

Figure A5. Correlation of normalized mean values per hour of measured charging events from Hecht et al. 2020 [40] and the Agent-based e-Mobility Model over the course of a week.

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